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Yuping Duan[1,2*], Gouenou Coatrieux[2], Huazhong Shu[1,3]

[1]Laboratory of Image Science and Technology, Southeast University, Nanjing 210096, China.
[2]Institut Mines-Telecom, Telecom Bretagne, INSERM U1101 Latim, Brest, F-29238, France.
[3]Centre de Recherché en Information Médicale Sino-français (CRIBs).
[*] Corresponding author, e-mail: duanyp11@gmail.com, tel: (+86)15996213226.

Abstract* –*In this paper, we propose a system for the identification of the system that has produced a Digital Radiography (DR) image. It takes advantage of the statistical properties of the noise left by any DR systems. In particular, a three parameter exponential model of the relationship in-between the image intensity and the overall noise variance is suggested. Its parameters are used as input of a classifier learned in order to discriminate different DR systems. Experiments conducted on images issued from 5 different DR systems show it is possible to identify with good accuracy the origin of one DR image.

Index terms - Image Processing, Modeling, X-Ray imaging

I. INTRODUCTION

The development of digital medical imaging technology (modalities, processing, transmission) makes images act an important role in cares. However such ease of manipulations induces security issues in terms of data confidentiality, authenticity, traceability and so on [1]. In this paper, we focus on the particular problem of Digital Radiography (DR) image origin identification that is to say being able to identify the DR system that issued an image. Even though DICOM (medical.nema.org) traces image modifications and transmissions by means of "indicators" in the image file header, these latter can be accidentally or malevolently removed or changed [2]. Thus, how can we verify the origin of an image only from its pixels' gray values?

Many methods have been proposed to solve this problem for general public devices. Most of them analyze some characteristics that are specific to one chain of image acquisition. As example, Color Filter Array interpolation [3] or demosaicing [4] leave traces that can be used as digital forensics image fingerprints. However, with these methods, it is hard to distinguish different devices model based on the same algorithm. To overcome this issue, it has been suggested to exploit the Photo Response Non-Uniformity noise generated by CCDs (Charge Coupled Device) as camera fingerprint [5] or to combine a two parameter noise model with the likelihood ratio test to identify the camera that has acquired the image [6].

In this paper, we extend the approach of [6] to DR acquisition systems proposing a more adapted three parameters exponential model so as to model the relationship that exist in-between the image intensity and the variance of the DR image noise. Model parameters are then use as input of a classifier learned so as to discriminate different DR image systems.

The rest of this paper is organized as follows. Before presenting our system we come back on the modeling of the noise inherent to DR images in Section 2. Some experimental results are then presented in Section 3 and section 4 concludes this paper.

II. MATERIALS AND METHODS

II.1. Modeling noise in Digital Radiography Images

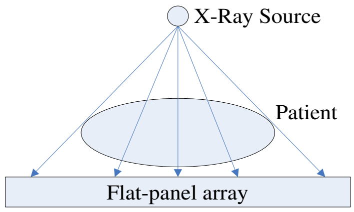

Figure 1: Digital radiograph system principles - a tight beam of X-rays source go through the patient, and then a flat-panel array layer converts the X-Rays' energy into electronic charges next read out so as to obtain a digital image.

Based on the strong similarities of DR acquisition systems with digital cameras, a generic signal-dependent noise observation model [7] can be considered

$$Y = I + \sigma(I)\cdot\xi \quad (1)$$

where Y is the acquired image, I is the real observed "scene", $\sigma(I)\cdot\xi$ is the noise term which can be further decomposed into

$$\sigma(I)\cdot\xi = \eta_p(I) + \eta_g \quad (2)$$

where $\eta_p(I)$ is a signal-dependent Poisson noise of variance varying with the intensity of I and η_g is a signal-independent Gaussian noise of constant variance. Contrarily to general public cameras for which the variance of the overall noise can be modelled through a linear expression (i.e., $\sigma^2(I) = a\cdot I + b$, with a and b two real parameters), a non-linear model has to be considered for DR images. The main reason stands on the non-parallel X-rays' incidence as shown in Figure 1. Based on the Poisson noise nature, the relationship between I and the noise variance $\sigma^2(I)$ can be modeled as

$$\sigma^2(I) = a\cdot\exp(b\cdot I) + c \quad (3)$$

More clearly, the variance of the noise varies exponentially with the image intensity. As we will see in the sequel *a*, *b* and *c* constitute the DR system fingerprint. They will be used to discriminate DR systems.

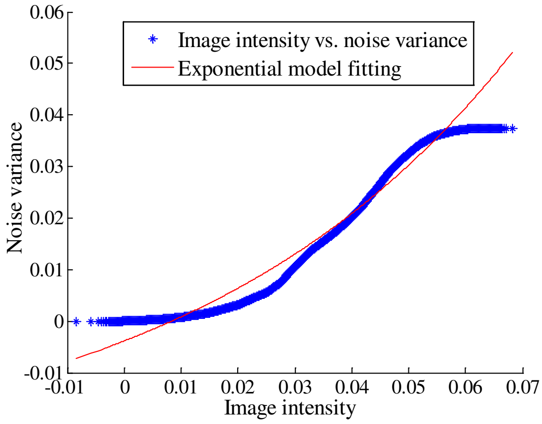

Fig.2 Relationship between the image intensity and noise variance of a Canon Orthopantomograph OC200D device and its fitting exponential model (*a*=0.0244, *b*=17.4839, *c*=-0.0282).

II.2. DR system identification

Here are the main steps our system follows: 1) it extracts the noise of a DR image Y by means of wavelet filtering [7], obtaining a noise image *N* which corresponds to the high-frequency wavelet coefficients of *Y*. The original "scene" is thus such as $I = Y - N$. 2) in order to reduce the noise estimation bias related to the presence of edges, those ones are discarded before noise analysis, masking them out with the help a binary mask created from N through morphology operators. 3) Only unmasked pixels of I and N are considered so as to build the relationship (3). Due to the fact I contains real pixels' values, its intensity dynamic is partitioned into regular intervals or bins $I_e(k)$. For one bin $I_e(k)$, its mean intensity $\overline{I_e}(k)$ is computed. $\overline{I_e}(k)$ is then associated to an unbiased estimator of the noise variance $\sigma^2(k)$ calculated on the pixels of N of same positions than the pixels of I belonging to $I_e(k)$. 4) Then, parameters *a*, *b* and *c* of our exponential model are estimated fitting the model by means of non-linear least squares (see Figure 2). 5) By next these parameters are provided to a SVM based classifier for DR system identification. Due to space limitation, this part of our system cannot be detailed.

III. RESULTS

To assess the above system effectiveness, 280 images issued from 5 DR devices were considered. The DR model and their corresponding image training and test sets' sizes are listed in Table 1. Performance, herein evaluated in terms of classification rates, are given in average after 5 tests in Table 2. As seen, our detection rate is about 96.37%. whatever the DR system.

IV. DISCUSSION – CONCLUSION

No.	Model	Training set size	Test set size
DR1	Canon Orthopantomograph OC200D	20	46
DR2	Canon Lorad Selenia	20	24
DR3	Thales Duet DRF	20	39
DR4	Thales Flashscan	20	29
DR5	Apelem PALADIO Versa	20	42

Table 1: DR system and SVM training and test set sizes.

DR	DR1	DR2	DR3	DR4	DR5
DR1	**95.22**	4.78	0	0	0
DR2	8.33	**91.67**	0	0	0
DR3	0	0	**96.41**	3.59	0
DR4	0	0	0	**100**	0
DR5	0	0	1.43	0	**98.57**

Table 2: Classification rates.

In this paper, we have investigated an approach which identifies the source of digital images based on the statistical dependence of the image intensity with the noise variance. Contrarily to general public camera devices, we show that a three-parameter exponential model is more adapted for DR images than a linear one. Our experimental results indicate high detection performance of our method but further experiments have to be conducted so as to better establish its accuracy due to the fact our image test set is of quite limited size.

ACKNOWLEDGMENTS

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